

# Online Handwritten Devanagari Stroke Recognition Using Extended Directional Features

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**Abstract**—This paper describes a new feature set, called the extended directional features (EDF) for use in the recognition of online handwritten strokes. We use EDF specifically to recognize strokes that form a basis for producing Devanagari script, which is the most widely used Indian language script. It should be noted that stroke recognition in handwritten script is equivalent to phoneme recognition in speech signals and is generally very poor and of the order of 20% for singing voice. Experiments are conducted for the automatic recognition of isolated handwritten strokes. Initially we describe the proposed feature set, namely EDF and then show how this feature can be effectively utilized for writer independent script recognition through stroke recognition. Experimental results show that the extended directional feature set performs well with about 65+% stroke level recognition accuracy for writer independent data set.

## I. INTRODUCTION

Interest in handwritten script recognition [1], [2], [3] and specifically in online handwritten script recognition [4], [5], [6] has been active for a long time. In the case of Indian languages, research works are active especially for Devanagari [7], Bangla [8], [9], Telugu [10] and Tamil [11], [12]. Devanagari script, the most widely used Indian script, consists of vowels and consonants as shown in Fig. 1. It is used as the writing system for over 28 languages including Sanskrit, Hindi, Kashmiri, Marathi and Nepali and used by more than 500 million people world wide. Devanagari is written from left to right in horizontal lines and the writing system is alphasyllabary. Barring a few alphabets, almost all the alphabets in English can be written in a single stroke<sup>1</sup> or two. In contrast, in most Indian languages, alphabets are made up of two or more strokes. This writing requirement makes it necessary to analyze a sequence of adjacent strokes to identify an alphabet. Majority of the alphabets in Devanagari script are formed by using multiple strokes. Language syllables are composed of vowels, consonants and their combinations. In a consonant-vowel combination, the vowels are orthographically indicated by signs called *matras*. These modifier symbols are normally attached to the top, bottom, left or right of the base character. Hence the consonants, vowels, matras and consonant/vowel modifiers constitute the entire alphabet set. These composite

<sup>1</sup>A stroke is defined as the resulting trace between a pen-down and its adjacent pen-up



Fig. 1. Devanagari alphabet set [13].

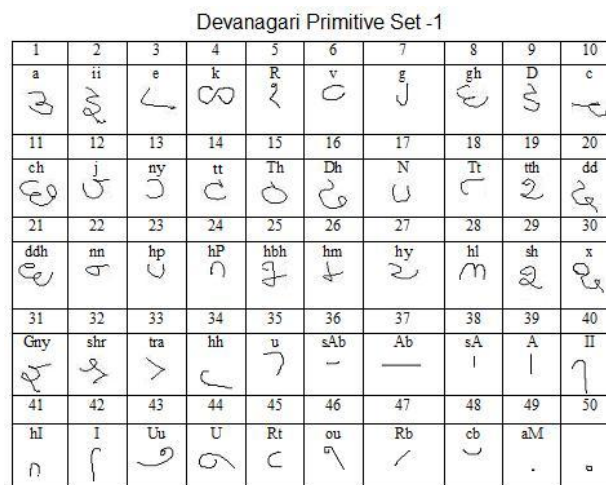


Fig. 2. A set of *primitives* hand written strokes that can be used to write the complete alphabet set in Devanagari.

characters are then joined together by a horizontal line, called *shirorekha*.

A careful analysis based on clustering of handwritten Devanagari script showed that there was a *basis like* set of 50 strokes that was sufficient to represent all the alphabets in the Devanagari script. We name these strokes *primitives*. The identified set of primitives (shown in Figure 2) can be used to write the complete Devanagari alphabet set (Figure

Sr. No.	Character	Handwritten Samples					
		1	2	3	4	5	6
1.	३	3	3	3	3	3	3
2.	५	5	5	5	5	5	5
3.	८	8	8	8	8	8	8
4.	७	7	7	7	7	7	7
5.	२	2	2	2	2	2	2
6.	४	4	4	4	4	4	4
7.	६	6	6	6	6	6	6
8.	९	9	9	9	9	9	9
9.	०	0	0	0	0	0	0
10.	१	1	1	1	1	1	1

Fig. 3. Sample set of *primitives* collected from a single writer.

1). In this paper we use these *primitives* as the units for recognition taking parallel from the recognition of *phone set* used in speech recognition literature. In an unconstrained handwriting these *primitive* strokes exhibit large variability in shape, direction and order of writing. It is also observed that the *primitives* are combined and broken based on the writer's style of writing which is acquired at the time of learning the script. A sample set of *primitives* collected from the same writer at different times over a period of time is shown in Figure 3. The variations within the *primitives* even for the *same* writer is evident and it is observed that the variation among different writers is even larger; making the task of recognizing these *primitives* challenging.

While a large amount of literature is available for online handwriting recognition of English, Chinese and Japanese languages, until recently, relatively very less work has been reported for the recognition of Indian languages [6], [5], [4]. Even among the Indian scripts, notable work has been reported only for Devanagari [14], Bangla [8], Tamil and Telugu scripts [15], [10]. It is also observed that the work done on one Indian language script cannot be directly applied for the recognition of a second language script because of the vast variation in the scripts. The main challenge in online handwritten character recognition in Indian language is the large size of the character set, variation in writing style (when the same stroke is written by different writers or the same writer at different times) and the visual similarity between different alphabets in the script. A list of visually similar alphabets in Devanagari script are shown in Figure 4.

In this paper, we propose the use of extended directional feature (EDF) set for the recognition of *primitives* (which are also called strokes). The variations that exist in the *primitives* (see Figure 3) test the credibility of the proposed features. The motivation to look at recognition of strokes rather than looking at alphabet recognition is influenced by

Sr. No.	Confusing Characters
1.	३ ५ ८ ७
2.	२ ४
3.	९ ० १
4.	२ ४
5.	८ ७ ६ ५
6.	२ ४ ७ ८

Fig. 4. A list of some confusing alphabets in Devanagari.

the speech recognition literature. The strokes are analogous to phonemes in speech. It is well known in speech literature that though the phoneme recognition accuracies are poor (it is about 20% in singing voice [16]), the final output of the speech recognition is significantly high. The poor phoneme recognition in speech recognition is enhanced by lexicons and statistical language models. We believe that even a poor stroke recognition accuracies can lead to very high alphabet recognition accuracies when knowledge about the written language is exploited. The rest of the paper is organized as follows. We introduce the extended directional feature set in Section II, in addition a detailed explanation of data collection, pre-processing. Experimental results are outlined in Section III, and conclusions in Section IV.

## II. EXTENDED DIRECTIONAL FEATURE EXTRACTION

Several temporal features [17], [18] have been used for script recognition in general and for online Devanagari script [19] recognition in particular. We propose a simple yet effective feature set based on extended directional chain code. The detailed procedure for obtaining these directional features is given below.

Let the online stroke be represented by a variable number of 2D points which are in a time sequence. For example an online stroke would be represented as

$$\{(x_{t_1}, y_{t_1}), (x_{t_2}, y_{t_2}), \dots, (x_{t_n}, y_{t_n})\}$$

where,  $t$  denotes the time and assume that  $t_1 < t_2 < \dots < t_n$ . Equivalently we can represent the online stroke (see Figure 5) as

$$\{(x_1, y_1), (x_2, y_2), \dots, (x_n, y_n)\}$$

by dropping the variable  $t$ . The number of points denoted by  $n$  vary depending on the size of the stroke and also the speed with which it was written. Most handwritten script digitizing devices (popularly called electronic pen or e-pen) sample the handwritten stroke uniformly in time. For this reason, the number of points per unit length of a handwritten stroke is large when the writing speed is slow which is especially true at curvatures (see Figure 5) and vice-versa.

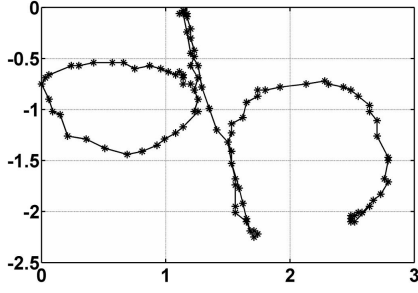


Fig. 5. A sample online character. The "\*" represent the  $(x, y)$  points, the points have been joined to give a feel for the stroke.

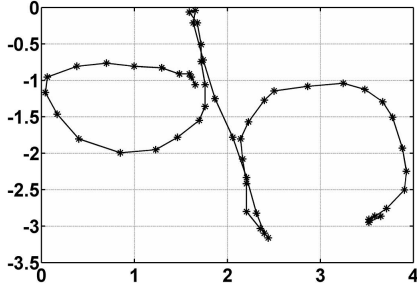


Fig. 6. After smoothing Figure 5 using Discrete Wavelet transform.

We first identify the curvature points (also called critical points) from the smoothed (we use discrete wavelet transform, we could have used any noise removal technique [20], see Figure 6) handwriting data. The sequence  $(x_i, y_i)_{i=0}^n$  represents the handwriting data of a stroke. We treat the sequence  $x_i$  and  $y_i$  independently and compute the curvature points for each of these sequence. For the  $x$  sequence, we calculate the first difference

$$x'_i = \text{sgn}(x_i - x_{i+1})$$

where

$$\begin{aligned} \text{sgn}(k) &= +1 & \text{if } x_i - x_{i+1} > 0 \\ \text{sgn}(k) &= -1 & \text{if } x_i - x_{i+1} < 0 \\ \text{sgn}(k) &= 0 & \text{if } x_i - x_{i+1} = 0 \end{aligned}$$

We use  $x'$  to compute the curvature point. The point  $i$  is a curvature point iff

$$x'_i - x'_{i+1} \neq 0.$$

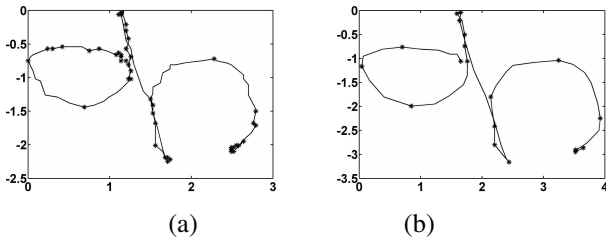


Fig. 7. Curvature Point extraction. (a) Raw online character and (b) after smoothing using Discrete Wavelet transform.

Similarly we calculate the curvature points for the  $y$  sequence. The final list of curvature points is the union of all the points marked as curvature points by both the  $x$  and the  $y$  sequence (see Figure 7). Clearly the number and position of the curvature points are more consistent and occur at the points where there is a change in curvature for smoothed stroke (Figure 7(b)) when compared to a raw stroke (see Figure 7(a)). It must be noted that the position and number of curvature points computed for different samples of the same stroke may vary.

Let  $k$  be the number of curvature points (denoted by  $c_1, c_2, \dots, c_k$ ) extracted from a stroke of length  $n$ ; usually  $k \ll n$ . The  $k$  curvature points form the basis for extraction of the extended directional features. We first compute the angle between the two curvature points, say  $c_l$  and  $c_m$ , as

$$\theta_{lm} = \tan^{-1} \left( \frac{y_l - y_m}{x_l - x_m} \right)$$

Now the extended directional feature set is computed by computing the direction between the curvature points as shown in Figure 8. Where  $d_{lm}$  corresponding to the angle  $\theta_{lm}$  (computed using the Algorithm 1) and is the direction between the curvature point  $c_l$  and  $c_m$ .

**Algorithm 1** Angle between two curvature point conversion into direction

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```

int deg2dir(double  $\theta$ )
int dir = -1;
if ( $\theta > -\pi/8$  &  $\theta < \pi/8$ ) then
    dir = 1;
end if
if ( $\theta \geq \pi/8$  &  $\theta < 3\pi/8$ ) then
    dir = 2;
end if
if ( $\theta \geq 3\pi/8$  &  $\theta < 5\pi/8$ ) then
    dir = 3;
end if
if ( $\theta \geq 5\pi/8$  &  $\theta < 7\pi/8$ ) then
    dir = 4;
end if
if ( $(\theta \geq \frac{7\pi}{8} \text{ \& } \theta < \frac{9\pi}{8}) \parallel (\theta \geq -\frac{9\pi}{8} \text{ \& } \theta < -\frac{7\pi}{8})$ ) then
    dir = 5;
end if
if ( $\theta \geq -7\pi/8$  &  $\theta < -5\pi/8$ ) then
    dir = 6;
end if
if ( $\theta \geq -5\pi/8$  &  $\theta < -3\pi/8$ ) then
    dir = 7;
end if
if ( $\theta > -3\pi/8$  &  $\theta < -\pi/8$ ) then
    dir = 8;
end if
return(dir);

```

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Given,  $k$  curvature points, we get (see Figure 8) an extended

CP	$c_1$	$c_2$	$c_3$	$c_4$	$\cdots$	$\cdots$	$c_m$	$\cdots$	$c_k$
$c_1$	0	$d_{12}$	$d_{13}$	$d_{14}$	$\cdots$	$\cdots$	$d_{1m}$	$\cdots$	$d_{1k}$
$c_2$	—	0	$d_{23}$	$d_{24}$	$\cdots$	$\cdots$	$d_{2m}$	$\cdots$	$d_{2k}$
$c_3$	—	—	0	$d_{34}$	$\cdots$	$\cdots$	$d_{3m}$	$\cdots$	$d_{3k}$
$c_4$	—	—	—	0	$\cdots$	$\cdots$	$\cdots$	$\cdots$	$d_{4k}$
$\vdots$	$\vdots$	$\vdots$	$\vdots$	$\vdots$	$\vdots$	$\vdots$	$\vdots$	$\vdots$	$\vdots$
$c_l$	—	—	—	—	$\cdots$	$\cdots$	$d_{lm}$	$\cdots$	$d_{lk}$
$\vdots$	$\vdots$	$\vdots$	$\vdots$	$\vdots$	$\vdots$	$\vdots$	$\vdots$	$\vdots$	$\vdots$
$c_k$	—	—	—	—	—	—	—	—	0

Fig. 8. Extended Directional Features

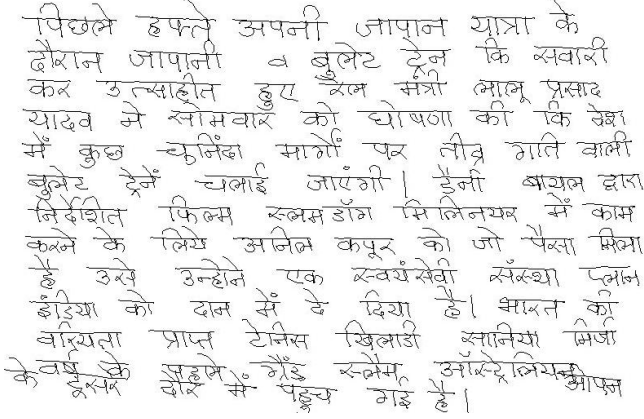


Fig. 9. Paragraph of online data collected from a user.

directional feature (EDF) vector of size

$$\frac{k(k-1)}{2}.$$

In all our experiments we have used this extended directional feature set to represent a stroke.

### III. EXPERIMENTAL ANALYSIS

For experimental analysis, we collected data from 10 persons, each of whom wrote a paragraph of Hindi text using Mobile e-Notes Taker (see for example, Figure 9). The mobile e-note taker is a portable pen based handwriting capture device which allows user to write on a normal paper using the electronic pen to capture the online handwritten text. The SDK provided with the device enables extraction of the  $x, y$  trace of the online handwriting data. In addition to the  $x, y$  trace the pen captures the pen-up and pen-down information which helps identify a stroke. Each stroke is characterized by a  $x, y$  sequence between a pen-down and a pen-up point. This raw stroke level data is smoothed using Discrete Wavelet Transform (DWT) decomposition, as mentioned earlier we do not dwell on this in this paper since this is well covered in pattern recognition literature, to remove noise in terms of small undulation due to the sensitiveness of the sensors on the electronic pen. For each stroke we extracted the extended directional feature set as described in Section II.

We used 5 user paragraph data for training and the other (not part of training) 5 for the purpose of testing the performance

of the ED feature set. We constructed a total of 252 ( $^{10}C_5$ ) sets of training and test data. We initially hand tagged each stroke in the collected data using the 50 *primitives* that we selected (see Figure 2). The strokes that did not fall into this *primitive* set were marked as being out of vocabulary. All the strokes corresponding to the given *primitive* in the training data was collected and clustered together. We retained those *primitives* that occurred atleast 10 times in the train and the test data and the rest of the *primitive* were not used for training and testing. In all we were able to get 20 *primitives* which occurred atleast 10 times in both the training and the test data set. While the dataset is not very large, the 252 different runs demonstrates the effectiveness of EDF in recognition of the *primitives*.

As a next training step, we calculated the dynamic time warping (DTW) distance between all strokes corresponding to the same *primitive* (numbering 20). Note that different strokes corresponding to the same *primitive* had different ED length and hence to compute the distance between the two strokes we need to use DTW algorithm<sup>2</sup>. All strokes corresponding to the same *primitive* which were within a distance of  $\tau$  were clustered together and only one representative stroke from the cluster was retained as the cluster representative. We chose  $\tau$  such that for each *primitive* there were a maximum of 3 sample strokes. So for a set of 20 *primitives* we had a reference set of 60 samples.

For testing purpose, we took a test stroke ( $s_t$ ) from the test data, we first extracted EDF and compared it with the EDF of the 60 reference strokes using DTW algorithm. We choose 2 different methods to assign the test stroke into one of the 20 *primitives* (classification).

- Method I: The stroke  $s_t$  is classified as a *primitive*  $p^*$  such that the DTW distance of  $s_t$  with the *primitive*  $p^*$  is minimum

$$\min_{p^*} \left\{ d(s_t, p_i)_{i=1}^{60} \right\}$$

Note  $d(a, b)$  is the DTW distance between  $a$  and  $b$ .

- Method II: The stroke  $s_t$  is compared with all the 60 reference strokes and the distance  $d(s_t, p_i)$  for  $i = 1, \dots, 60$  computed. We then take the average distance of the stroke from all the 3 references of a *primitive*. We arrange these average distances (20 in number) in the increasing order of magnitude. The *primitive* with the least average distance from the test stroke  $s_t$  is declared as being recognition of stroke  $s_t$ .

Table I shows the average number of strokes in the test data set corresponding to the 20 selected *primitives*. All the experimental results are based on this data set (from 10 people but run 252 times). The overall average stroke level recognition accuracies for both Method I and Method II did not vary significantly and stood at 65.6 % and 65.9 % respectively. Meanings on an average 410 for Method I and 412 for Method II of the 625 strokes were correctly recognized. Details of the average recognition are captured in Table II. It should be noted

<sup>2</sup>We do not discuss this algorithm, in detail since it is well used in online script recognition literature [21].

TABLE I  
AVERAGE (OVER 252 RUNS) NUMBER OF STROKES UNDER EACH *primitive*  
IN THE TEST DATA SET.

Primitive	Test
R	71
l	18
k	57
nn	67
v	36
p	36
dd	50
m	50
tt	23
y	36
aa	28
h	16
T	25
g	25
D	21
e	16
j	18
ii	10
ch	11
c	11
Total	625

TABLE II  
AVERAGE (OVER 252 RUNS) RECOGNITION ACCURACIES FOR TEST DATA  
SET.

Primitive	# Test	# recognized Method I	# recognized Method II
R	71	46	40
l	18	7	9
k	57	51	53
nn	67	36	34
v	36	23	26
p	36	32	32
dd	50	34	36
m	50	36	40
tt	23	11	13
y	36	22	20
aa	28	25	20
h	16	9	9
T	25	15	16
g	25	10	12
D	21	13	15
e	16	7	5
j	18	13	13
ii	10	4	5
ch	11	9	8
c	11	7	6
Total	625	410	412

that the accuracies are writer independent and for stroke level recognition.

#### IV. CONCLUSIONS

In this paper we have introduced a new online feature set, called the extended directional feature. Based on the extensive experimentation (252 runs) on a set of strokes captured from a set of 10 people, we observe that this feature set is capable of discriminating similar looking strokes quite well. We have presented recognition accuracies for writer independent stroke level data set. It is well known, both in speech and script

recognition literature that stroke (phoneme in case of speech) recognition is always poor. However like in speech where the phone recognition is improved by using lexicon and statistical language model, we plan to cluster strokes using spatio-temporal information to form alphabets and then use the cluster of strokes to classify them into an alphabet. This we believe will lead to good accuracies of writer independent script recognition. Further the derived *primitives* set are not language dependent and can be used for recognition of other languages albeit with a different *primitive* set.

#### REFERENCES

- [1] Sebastiano Impedovo, "More than twenty years of advancements on frontiers in handwriting recognition," *Pattern Recogn.*, vol. 47, no. 3, pp. 916–928, Mar. 2014.
- [2] Mohammed Cheriet, Nawwaf Kharma, Cheng-lin Liu, and Ching Suen, *Character Recognition Systems: A Guide for Students and Practitioners*, Wiley-Interscience, 2007.
- [3] Réjean Plamondon and Sargur N. Srihari, "On-line and off-line handwriting recognition: A comprehensive survey," *IEEE Trans. Pattern Anal. Mach. Intell.*, vol. 22, no. 1, pp. 63–84, Jan. 2000.
- [4] Rituraj Kunwar and A. G. Ramakrishnan, "Online handwriting recognition of tamil script using fractal geometry," in *Proceedings of the 2011 International Conference on Document Analysis and Recognition*, Washington, DC, USA, 2011, ICDAR '11, pp. 1389–1393, IEEE Computer Society.
- [5] J. Rajkumar, K. Mariraja, K. Kanakapriya, S. Nishanthini, and V. S. Chakravarthy, "Two schemas for online character recognition of telugu script based on support vector machines," in *Proceedings of the 2012 International Conference on Frontiers in Handwriting Recognition*, Washington, DC, USA, 2012, ICFHR '12, pp. 565–570, IEEE Computer Society.
- [6] Amit Arora and Anoop M. Namboodiri, "A hybrid model for recognition of online handwriting in indian scripts," in *Proceedings of the 2010 12th International Conference on Frontiers in Handwriting Recognition*, Washington, DC, USA, 2010, ICFHR '10, pp. 433–438, IEEE Computer Society.
- [7] N. Joshi, G. Sita, A.G. Ramakrishnan, V. Deepu, and S. Madhvanath, "Machine recognition of online handwritten Devanagari characters," in *ICDAR05*, 2005, pp. II: 1156–1160.
- [8] S.K. Parui, K. Guin, U. Bhattacharya, and B.B. Chaudhuri, "Online handwritten bangla character recognition using HMM," in *Pattern Recognition, 2008. ICPR 2008. 19th International Conference on*, Dec 2008, pp. 1–4.
- [9] U. Bhattacharya, B.K. Gupta, and S.K. Parui, "Direction code based features for recognition of online handwritten characters of Bangla," in *ICDAR07*, 2007, pp. 58–62.
- [10] V. Babu, L. Prasanth, R. Sharma, G. V. Rao, and A. Bharath, "HMM-based online handwriting recognition system for telugu symbols," In *9th International Recognition (ICDAR 2007)*, 23–26 September, Curitiba, Paraná, Brazil [22], pp. 63–67.
- [11] S. Sundaram and A. Ramakrishnan, "A novel hierarchical classification scheme for online Tamil character recognition," in *ICDAR07*, 2007, pp. 1218–1222.
- [12] A. Bharath and S. Madhvanath, "Hidden markov models for online handwritten Tamil word recognition," in *ICDAR07*, 2007, pp. 506–510.
- [13] Verbix, "Misc languages: Hindi," <http://www.verbix.com/languages/hindi.shtml>, 2010, [Online; accessed 29-June-2010].
- [14] H. Swethalakshmi, C. Chandra Sekhar, and V. Srinivasa Chakravarthy, "Spatio-structural features for recognition of online handwritten characters in devanagari and tamil scripts," in *Artificial Neural Networks - ICANN 2007, 17th International Conference, Porto, Portugal, September 9–13, 2007, Proceedings, Part II*, Joaquim Marques de Sá, Luís A. Alexandre, Włodzisław Duch, and Danilo P. Mandic, Eds. 2007, vol. 4669 of *Lecture Notes in Computer Science*, pp. 230–239, Springer.
- [15] L. Prasanth, V. Babu, R. Sharma, G. V. Rao, and Dinesh M., "Elastic matching of online handwritten tamil and telugu scripts using local features," In *ICDAR* [22], pp. 1028–1032.

- [16] Annamaria Mesaros and Tuomas Virtanen, "Recognition of phonemes and words in singing," in *Proceedings of the IEEE International Conference on Acoustics, Speech, and Signal Processing, ICASSP 2010, 14-19 March 2010, Sheraton Dallas Hotel, Dallas, Texas, USA*. 2010, pp. 2146–2149, IEEE.
- [17] Claus Bahlmann, "Directional features in online handwriting recognition," *Pattern Recognition*, vol. 39, no. 1, pp. 115 – 125, 2006.
- [18] Seiichi Uchida and Marcus Liwicki, "Analysis of local features for handwritten character recognition," in *Proceedings of the 2010 20th International Conference on Pattern Recognition*, Washington, DC, USA, 2010, ICPR '10, pp. 1945–1948, IEEE Computer Society.
- [19] V. L. Lajish and S.K. Kopparapu, "Fuzzy directional features for unconstrained on-line devanagari handwriting recognition," in *Communications (NCC), 2010 National Conference on*, Jan 2010, pp. 1–5.
- [20] V.L. Lajish, V.K. Pandey, and S.K. Kopparapu, "Knotless spline noise removal technique for improved oher," in *Signal and Image Processing (ICSIP), 2010 International Conference on*, Dec 2010, pp. 305–308.
- [21] Claus Bahlmann and Hans Burkhardt, "The writer independent online handwriting recognition system frog on hand and cluster generative statistical dynamic time warping," *IEEE Trans. Pattern Anal. Mach. Intell.*, vol. 26, no. 3, pp. 299–310, Mar. 2004.
- [22] *9th International Conference on Document Analysis and Recognition (ICDAR 2007), 23-26 September, Curitiba, Paraná, Brazil*. IEEE Computer Society, 2007.